Dynamic peak demand pricing under uncertainty in an agent-based retail energy market

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Abstract. For a transition to a sustainable energy future, smart grids must adapt to the mass introduction of renewable energy sources and their inherent unpredictability. The Power TAC competition is a simulation of distribution grid market dynamics with autonomous retail broker agents. It seeks to reflect real-world scenarios and thus guide policy and business decision-making. In Power TAC, these autonomous agents ("brokers") trade energy through markets and offer tariff contracts to retail customers who consume and produce energy. By periodic alignment with present real-world and alternative future scenarios, Power TAC utilizes the autonomous agent competition structure to investigate sustainable solutions to electricity supply questions. We explore how alignment activities between the 2014 and 2015 competition years, in particular adding a high volume of retail solar production, made net demand less predictable for brokers. It also made demand more volatile in the 2015 competition, leading to more extreme peak demand events. A principal alignment activity between 2015 and 2016 is the introduction of peak-demand charges for brokers. We design a new peak-demand pricing mechanism that reflects the costs of grid capacity usage, balancing real-world practice against the constraints of the simulation environment. We explore the effects of these changes on broker decisions that account for imbalance and peak demand.

Keywords: *smart grid, autonomous agents, energy markets, sustainability, peak demand*

1 Introduction

The conventional electricity supply chain produces energy in centralized, large-scale generation facilities, then processes and distributes it to individual retail and industrial consumers. However, with widespread adoption of renewable energy sources in the form of both large-scale mass generation facilities and small-scale retail packages, this conventional centralized approach has begun to lose relevance [18]. Many renewable sources have variable, weather-dependent energy output, and many, such as rooftop solar facilities, are widely distributed small units rather than large centralized generators. As a result, many energy customers are producing energy as well as consuming it. Renewables accounted for 142 terawatt-hours of German energy production in 2012 (23% of total), and Germany's long-term goal is 80% renewables penetration by 2050 [6]. The US state of California has set a 2020 target of 33 percent renewable energy production [7]. However, this fast adoption is not without risk.

The primary forms of renewable energy that are experiencing fast growth are wind and solar power. Though providing sustainable and renewable energy at essentially zero marginal cost, both these energy sources are heavily weather-dependent. Weather forecasting is at best stochastic and at worst lucky guesses, thus making the future output of these energy sources uncertain. On the demand side, electricity demand has been almost entirely inelastic, partly because electricity users pay a flat rate for energy, and have little or no visibility into their current or projected usage. Thus, the transmission and distribution grids face the difficult task of balancing inelastic demand and volatile supply [12].

Another task further complicated by introducing renewable energy sources, in particular solar power, is maintaining supply reliability in the face of demand peaks. In a given region, consumer energy consumption typically peaks in the morning when people are preparing for the day, and in early evening when they return home. In areas with high air-conditioning loads, peak demand may fall in the late afternoon when heat load peaks, and in areas that depend on electricity for winter heating, demand may peak at night when the heat load is highest. However, fixed solar energy installations typically follow a sinusoidal profile on sunny days, between sunrise and sunset, and may show considerable volatility on days with scattered clouds. In most areas, demand peaks do not coincide with peak output of solar panels. Hence, peak demand will remain a significant issue in the future.

An electricity distribution network's capacity must be designed to handle peak loads. Thus, grid capacity is generally dependent on demand at peak hours. However, the amount of energy that is transferred through the grid is regularly lower. With higher peaks, a larger portion of capacity investment is needed to prevent congestion, and this additional capacity is left under-used during non-peak demand. These capacity costs, which are mainly at the transmission level, trickle down from the distribution grid to individual customers as grid connection costs. As energy peak-to-average ratios increase, these costs take higher percentages of a customer's total energy bill. Thus, it is in consumer economic interest to mitigate peak demand.

There are quite a few methods proposed to tackle this issue. Smart grid technology has advanced to a degree that makes many possible solutions feasible [23]. However, these technologies differ in their actual practicality. Motivating small-scale users to shift their hourly energy use with time-of-use pricing does not currently seem promising [5, 11]. Another solution, the use of demand response resources, such as energy storage units, shows enormous potential [21], albeit lagging on actual current use [19]. Consequently, market mechanisms that encourage demand response resource use are a hot research topic.

Many studies have analyzed such market mechanism models [24, 17, 22]. However, most of these studies lag behind on reproducibility and verifiability, as their real-world data sources and simulation environments induce modeling biases that distort cross-study comparisons. In addition, the singularity of solving the research problem with one approach may leave unexplored the remainder of the design space. One suggested approach to minimize these biases and foster full exploration of the design space is through Competitive Benchmarking (CB) [16].

CB contains three central elements. The *Platform*, a shared foundation among a series of stakeholders, would in this case be a shared competitive simulation environment for a variety of participant researchers. *Alignment* is conducted periodically to improve the platform's various elements through reflection of and adaptation to real-world scenarios. *Process* activities involve integrating input as autonomous agents from participant stakeholders and running periodic competitions between these agents. Processes evaluate the performance of both the platform and the stakeholders' agents.

The Power Trading Agent Competition (Power TAC) [3] is a CB approach for simulating electricity market dynamics at the distribution level [13]. In Power TAC, autonomous agents (also known as "brokers") seek individual profits in a competitive retail market by brokering energy and resources in a distribution grid. By means of this "smart market" simulation, we can understand how a variety of market mechanisms, retail decisions, and real-world events can potentially affect the electricity supply chain [4]. Previously, Power TAC has been the testbed of research on Time-of-Use retail tariffs [25], autonomous agents [20, 8], and market strategy [3]. It is central for the applicability and quality of these research endeavors that the platform they are based upon retains relevance to the real world.

In past Finals competitions, the Power TAC simulation accounted for peak demand as a fixed capacity cost incurred by an agent's total energy transport through the distribution grid. However, this pricing scheme proved to have some drawbacks. It did not align well with real-world practice, where markets usually charge higher costs for higher electricity capacity use. It also did not suitably motivate autonomous brokers to suppress peak demand (i.e. flatten their demand). These findings suggested that an alignment activity was required to improve the pricing mechanism for peak demand.

In this research, we came across the following findings:

- Peak demand pricing is a significant missing element in the Power TAC simulation. In the 2015 competition, brokers did not balance their supply and demand well, and also generally did not utilize demand response resources. A lack of capacity charges based on peak demand may be a contributing factor to both.
- Some real world practices cannot be exactly implemented in an alignment activity. Thus, a suitable mechanism needs to reflect but not replicate the original practice. We analyze and discuss the possible implications of this differing activity.

[3] see www.powertac.org

– We explain and offer the peak demand pricing mechanism for Power TAC 2016 as an alternative method for pricing capacity use in the real world.

In this article, we elaborate on a new pricing mechanism for grid capacity use based on peak demand. We first provide some background information on capacity pricing and peak demand in Section 2. We describe the Power TAC competition's simulation environment in Section 3. Section 4 follows with a detailed explanation of the analysis that led to the pricing mechanism. We conclude with a brief overview of this analysis' limitations and possible future work in Section 5.

2 Background on Capacity Pricing

Energy delivery in an electricity supply chain is done in two parts. First the transmission grid processes and dilutes generated electricity into voltages that can be transported over long distances. This is generally done by entities known as Regional Transmission Organizations (RTO) or Independent System Operators (ISO) in the United States, and by Transmission System Operators (TSO) in Europe. Next, the distribution grid further adjusts the alternating current voltage to values that make the electricity usable by end consumers. Most costs incurred in energy transportation are from investments and operations and maintenance activities at the transmission level. These costs are passed down to the distribution grid operators, who in turn charge consumers for their contribution to capacity use.

In the real world, grid operators usually charge end consumers based on their contribution to a series of peak demand in some prior timespan. This is usually mandated by the transmission level operator to the distribution grid's load serving entities (LSE), who then divides this charge based on each consumer's energy consumption share. For example, in the United States, one LSE charges customers connected to the Midwest Independent System Operator (MISO) grid for their contribution to a monthly demand peak. However, their customers who are connected to the Pennsylvania Jersey Maryland Interconnection (PJM) get charged based on 5 peak hours in the previous year with a similar energy share cost. For the New York Independent System Operator (NYISO) and New England Independent System Operator's (ISO-NE) connections, they consider only the maximum peak hour in the previous year.[4]

There does not appear to be much research on peak demand fees and how such a pricing mechanism should be formed in a competitive energy market. It appears to us that such a research topic has been left relatively under-studied. Feldman et al conducted a short case study of the potential savings if peak demand is reduced or held constant using demand response resources [10]. Their regional scope was the US states of Illinois and Massachusetts. They conclude that the costs for DR resources associated with these controls are much less than

[4] see www.directenergybusiness.com/landing/pdf/UNDERSTANDING-CAPACITY.pdf

the potential economic benefits of reducing peak demand. Aside from this, there is little research on how various pricing mechanisms impose costs and benefits upon various stakeholders.

3 The Power Trading Agent Competition

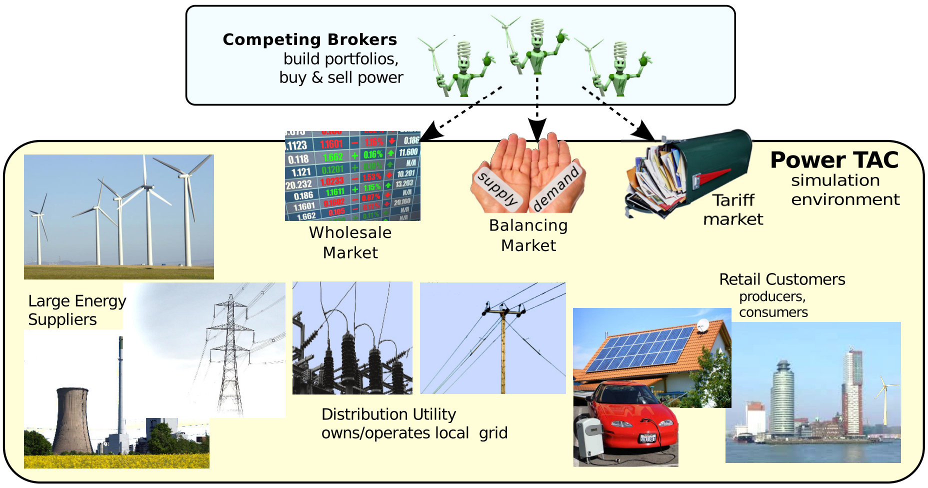

Fig. 1. Schematic diagram of the Power Trading Agent Competition (from [14]).

Power TAC is a competitive simulation of a retail electricity market. Within a CB platform, autonomous broker agents trade energy and resources with various entities (Figure 1), including residential and business consumers as well as demand response facilities. Trading happens through a wholesale market, a balancing market, and a retail tariff market. Each broker seeks profit maximization by balancing an energy supply and demand. Brokers have many resources that can be utilized to this end, but power generally flows from purchases in the wholesale market through tariff subscriptions to consumer subscribers.

The competition normally consists of a tournament of games. Each game is a competition between various brokers in the simulation environment. In Power TAC 2015 and 2014, this environment simulated a small city with a population of about 100000 people over a period of about 8 1/2 weeks. Broker actions, demand and supply, and market dynamics are segmented into time slots of one hour. Weather forecasting is borrowed from real-world data of an undisclosed location, which is used to influence the generation of weather-dependent energy sources. To focus on the economic aspects of market design, most physical limitations of electricity grids are simplified in Power TAC. Within the confines of the Power TAC markets and the tariff guidelines, brokers are free to employ all market capabilities to obtain a higher overall profit. More information on the Power TAC 2015 competition can be found in the game specification [14]

3.1 The Retail Tariff Market

Broker revenues and demand is generally expected to come through the retail tariff market. Within this market, brokers publish tariffs, which are evaluated by customers, who then choose among the most economically rational tariffs (There is however some customer choice uncertainty and random churn). These tariffs bind brokers to supply energy (or in the case of producers, purchase energy) to the tariff subscribers, who are in turn expected to pay (or for producers, receive) the costs associated with their energy delivery.

Brokers have a variety of options for customizing customer tariffs. Time-of-use pricing, dynamic pricing, tiered pricing, and capacity controls (i.e. demand response resources) are among the more interesting from a research perspective.

Customers evaluate tariffs on a non-persistent basis. Their choice to evaluate published tariffs is expected to follow a probability function that is reset to 0 when a tariff is subscribed to and increases gradually over time. The customers' tariff evaluation follows a utility estimation function. This utility function depends on the published tariff's details and gives a specific utility value for each tariff. This value is compared against an inconvenience factor, which accounts for customer disfavor to switch tariffs or brokers and for certain tariff types (such as inconvenience from time-of-use pricing). If the utility gain of a tariff exceeds the inconvenience of the tariff itself and of switching tariffs, the customer switches to that tariff.

A broker's subscriber portfolio can consist of energy consumers, energy producers, and demand response resource providers. Some subscribers can be a combination of the three, but subscribers mainly consume energy.

3.2 The Wholesale Market

The Power TAC wholesale market operates similar to most traditional energy exchange markets. It functions based on a periodic double auction, similar to the NordPool or FERC [2]. Within each hour of the simulation, each broker can place an order for purchase (ask) or sale (bid) of energy for any of the next 24 hours. Thus, in each timeslot, the market may need to process bids or asks from the previous 1 to 24 timeslots. These offers must contain energy quantity information, but do not need to necessarily contain price information. That is, a broker may bid for x kilowatt hours of energy without any price, or at price y per kilowatt hour. Bids and asks are matched in order of price, and the last matched bid and ask define the market's clearing price for that timeslot. Every bid and ask is processed at this price. Thus, a broker that has not specified a price in their ask (bid), must pay (will receive) whatever price the market clears at. If the last bid is partially matched with an ask, only the matched energy amount will be transacted.

In addition to the brokers, two other market participants trade in the wholesale market:

- Generation companies, or *Gencos*, are wholesale energy suppliers. In the previous competitions, an abstract Genco entity also submitted a multitude of bids and asks that simulated a quadratic supply curve. The coefficients of the quadratic curve vary over time through a mean-reverting random walk. The Genco's bid quantities are selected from a normal distribution.
- An external *Buyer* trades energy on behalf of parties outside the scope of the simulation. This Buyer entity is mainly meant to provide liquidity to brokers who wish to sell energy through bids. The Buyer's bids also add some uncertainty to market clearing prices.

In Power TAC, brokers are expected to obtain the bulk of their energy supply through the wholesale market. However, due to various uncertainties, in particular the unpredictability in supply arising from weather dependencies, they can sometimes have either excess or insufficient energy at the end of each timeslot. But an electricity grid requires near-perfect balancing at each moment, so a balancing market solves the grid imbalance problem.

3.3 The Balancing Market

In the Power TAC Simulation, after all market transactions between brokers and customers are carried out, a balancing market calculates broker imbalances and charges them accordingly. In this market, brokers are charged trading prices for imbalance that are much less appealing than wholesale market prices. However, they are also allowed here to utilize demand response resources through balancing orders. The process for choosing balancing orders is similar to a one-sided auction, and for each order that is cleared a VCG payment is computed against the other orders (more information in [9]).

The balancing market seeks to:

- motivate use of demand response resources for grid balancing,
- discourage carrying energy excess or deficiency into the balancing market, and
- encourage keeping a balance opposite to that of the (expected) total imbalance.

The balancing market is meant to respond to that portion of the supply and demand balancing problem that relates to unpredictability. That is, it is not meant to satisfy energy demand, but to compensate for inaccuracies in broker predictions, and reward better prediction algorithms. In the case that demand response resources are not enough to mitigate balancing, a regulating market entity provides additional balancing capacity. This entity trades at prices that are much less attractive than similar trades in the other markets.

4 Aligning Peak Demand Costs

Between each competition year of Power TAC, routine alignment activities recalibrate the real-world applicability of the simulation. These activities are also meant to maintain the simulation's suitability for research studies.

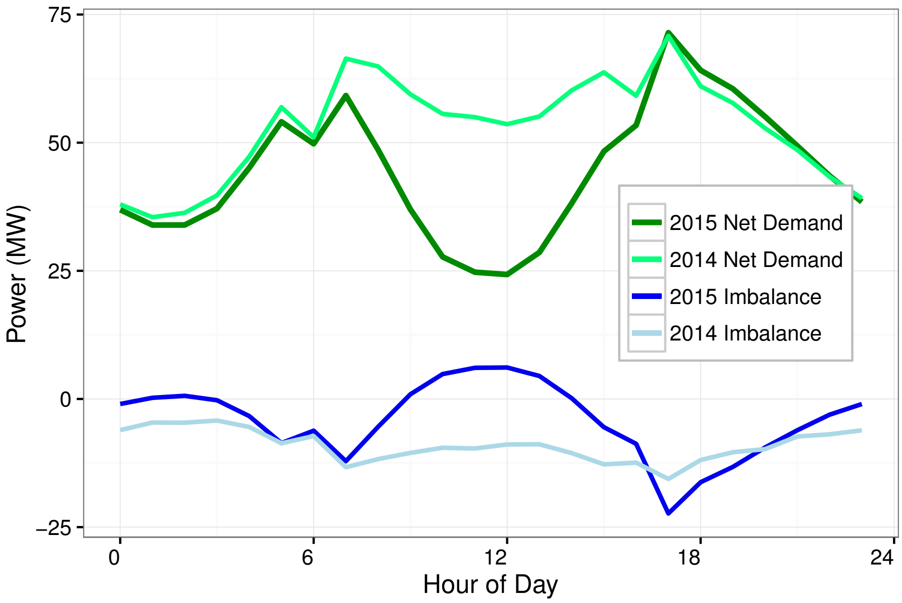

Fig. 2. Imbalance and net demand for the 2014 and 2015 Power TAC Finals competitions.

In this regard, to reflect a similar trend in the real world, the Power TAC 2014 competition year saw an introduction of capacity control capabilities for managing demand response. Likewise, the 2015 competition year saw the following additions:

- The advent of residential solar "prosumers", residential consumers who have added a solar photovoltaic electricity generation installation for their household.
- Addition of electric vehicle (EV) owners, who organize the use and charging of an EV and its use as demand response.
- Introduction of an electric forklift truck fleet model, which aggregates data from a fleet of electric forklifts operating in an industrial warehouse setting, as both a consumer and a demand response mechanism.

After analyzing the results of the 2015 Finals competition, we realized that brokers largely ignored the demand response resources. That is, they left imbalances in the balancing market for the regulating market entity to solve. Moreover, the sudden increase of solar prosumers drastically increased their imbalances and significantly decreased their net demand during daylight hours (Figure 2). Thus, the main alignment activity that changed the competition's dynamics was the first item, i.e. the advent of solar prosumers. How a sudden increase in solar production affected the imbalance market and its pricing mechanisms are studied in another research activity [1]. Here, we focus on capacity use by brokers.

In the real world, grid capacity is strongly dependent on the maximum total energy extracted from the transmission level by the distribution system operator (DSO). Most of these costs are incurred at the transmission level, where investments in generation facilities, power lines, and transmission station infrastructure dominate the costs of energy supply and transport. Modern electricity supply markets charge for capacity as a surcharge on electricity use. This surcharge is calculated as a function of maximum net demand during some time period in the past, usually in the timescale of months or years (details in Section 2). This pricing mechanism has inflexibility issues, however, in particular since daily demand curves (which typically resemble the demand plots in Figure 2) are strongly dependent on the time of year.

In the previous Power TAC Finals, capacity use was charged as a fixed surcharge through the wholesale market for electricity delivery. This fixed charge not only does not reflect similar pricing in the real world, but also does not set up a suitable correlation scheme between capacity use and actual maximum demand. Thus, we here discuss the setup of another pricing mechanism for Power TAC. This pricing scheme closely follows real-world cost structures, but retains some flexibility to allow for both its execution in the simulation and support research on dynamic peak demand pricing.

To find a suitable mechanism for pricing capacity, we first looked at the net demand in the 2014 and 2015 Finals competitions (Figure 3). This value is the energy expected to be pulled from the transmission system operator (TSO) by the DSO, and is directly correlated with actual delivery costs. Net demand for the 2014 competition showed an average of 52.95 MWh, with a standard deviation of 13.20 MWh, whereas the same values for the 2015 competition were 44.23 MWh and 17.25 MWh, respectively. These values were calculated over all games in each competition. The decrease in average and increase in standard deviation can both be attributed to the advent of residential solar producers.

To compare how the higher end of the net demand values appeared, we also studied peak demand. We defined peak demand as the maximum overall demand during each week of the simulation. Both the 2014 and 2015 Finals competitions showed a significant number of peak demand events (Figure 4). However, we found that peak demand events tend to not vary between competitions. Thus, they are not significantly related to the 2015 Finals' increase of residential solar. Also, peak demand appeared mostly in the early evening and occasionally in the early morning hours.

Based on these findings, we suggested the following pricing mechanism for capacity charges:

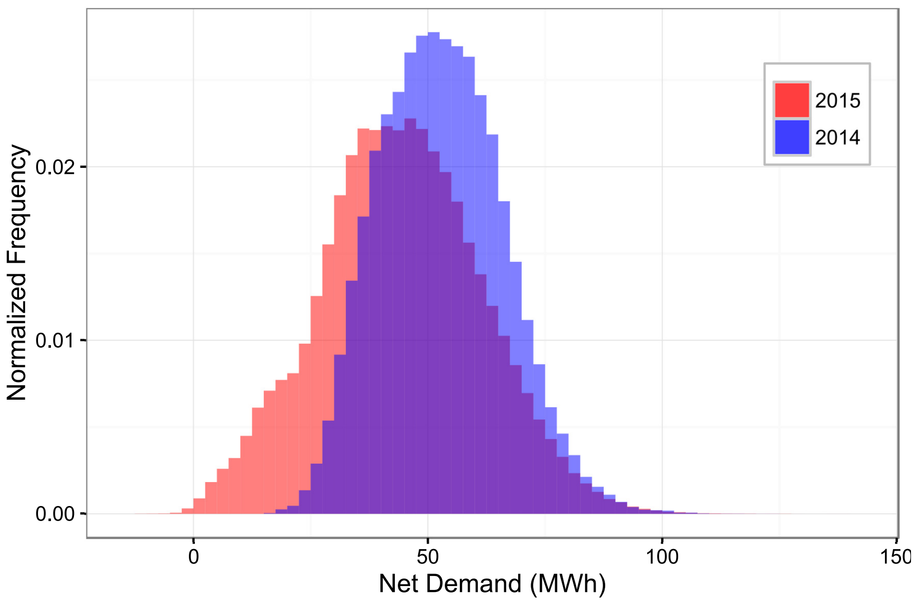

Fig. 3. Normalized net demand histograms for the 2014 and 2015 Power TAC Finals competitions.

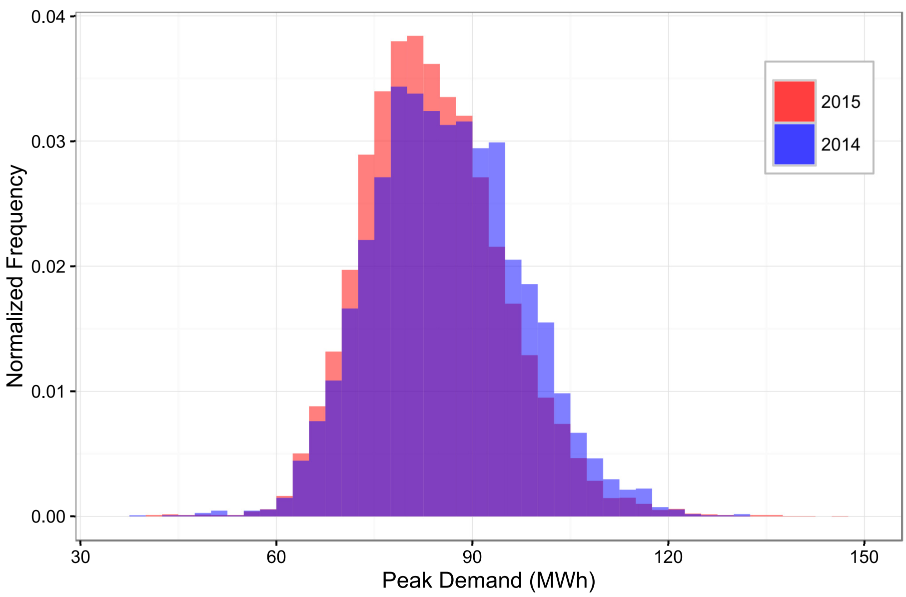

Fig. 4. Normalized peak demand histograms for the 2014 and 2015 Power TAC Finals competitions.

- First, brokers pay a small fixed fee per customer connection in each timeslot. This fee accounts for the capacity and the operations and management costs of the distribution grid. Small and large customers will pay different prices, since they utilize the distribution grid in somewhat different ways.
- Second, capacity charges will be computed at the end of each week, computing the highest n peaks in that week that go above a certain threshold. This threshold will be set to $mean_{demand} + 1.2 \times stdev_{demand}$, where $mean_{demand}$ and $stdev_{demand}$ are the average and standard deviation of demand in all prior timeslots. The amount that each peak exceeds the threshold is multiplied by a fee, and the resultant amount defines the peak demand charge. This peak demand charge is divided among brokers based on their demand share (i.e. the total demand of their contracted customers divided by the total demand) during that peak time.

The values of the fee for energy over the threshold and other parameters can be adjusted to suitably reflect real-world capacity costs.

The dynamic portion of the capacity charge would motivate brokers to both a) avoid demand in potential peak demand timeslots, and b)attempt to keep an energy demand portfolio that has more constant energy use on an hourly basis. Correctly applied, this mechanism is meant to smoothen the higher ridges of each day's demand curve. Although high demand is discouraged, low demand is not. Brokers can be expected to obtain portfolios farther from the generally expected daily demand plot. Thus, there is a possibility that more demand unpredictability will be introduced into the market with this addition. The resulting unpredictability of this addition can be an avenue of future research.

5 Conclusions and Future Work

The Power TAC simulation was designed to be a test bed for future energy trends. It seeks to both guide policy and business decisions and provide a basis for quantitative research on competitive energy markets. However, such a CB approach's value lies in retaining real-world applicability. This matter requires regular assessment through alignment activities.

In this article, we presented an alignment activity for the Power TAC 2016 competition year. We first discussed the potential need for a peak demand pricing mechanism within the simulation. We provided a pricing mechanism for the Power TAC simulation which is both feasible in the simulation environment and applicable to practice. This pricing mechanism has been implemented in the 2016 Power TAC competition year [15]. It has been calibrated to result in fees similar to those charged in real-world consumer energy bills. This mechanism's functionality and influence on Power TAC's dynamics will be assessed in the 2016 Finals competition in July 2016.

There are many possible research opportunities regarding the peak demand issue. One important investigation could be the effect of this new mechanism on Power TAC's market dynamics. We chose to implement a somewhat static capacity pricing option, to reflect similar pricing scenarios in the real world. However, other pricing mechanisms, such as dynamic pricing, could also be viable. Exploring other possible methods could introduce better methods for pricing capacity use. With the increased use of volatile renewable energy sources, the effect of these sources on peak demand also remains an open question. A study of regulation requirements for capacity pricing could also inform policy and legislation decisions.

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